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A Smart Energy Audit Framework Integrating BIM, IoT, and Multi-Criteria Decision Analysis for Building Energy Performance Optimization

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Abstract: Energy audits are key to improving energy efficiency and supporting decarbonization in buildings. Traditional audits rely on static data, manual inspections, and simple assumptions, which can limit their accuracy and usefulness. This study introduces an innovative energy audit framework that combines Building Information Modelling (BIM), Internet of Things (IoT) monitoring, and multi-criteria decision analysis (MCDA) to enhance the reliability and effectiveness of building energy assessments.

The proposed methodology combines BIM-based extraction of geometric and thermophysical building parameters with real-time operational data from IoT sensors. Key energy performance indicators, including specific energy consumption, potential energy savings, investment cost, payback period, and CO_2 emission reduction, are systematically evaluated. To support rational prioritization of energy efficiency measures, a weighted multi-criteria decision approach is applied, enabling transparent and reproducible ranking of retrofit and operational improvement options.

The results show that integrating digital building models and continuous monitoring significantly reduces uncertainty in energy performance evaluation compared to traditional audit methods. Control-oriented measures, such as HVAC optimization and intelligent lighting systems, offer the highest short-term benefits, while envelope retrofitting provides substantial long-term energy savings. The proposed framework offers a scalable, data-driven solution for modern energy audits and supports the transition toward smart, energy-efficient, and sustainable buildings.

Keywords: Energy audit; Smart buildings; BIM; IoT monitoring; Energy efficiency; Decision-making methods.

Introduction: Buildings are among the largest energy-consuming sectors worldwide, accounting for a substantial share of global final energy use and greenhouse gas emissions. Improving building energy efficiency is therefore a critical component of national and international decarbonization strategies and energy transition policies. In this context, energy audits are widely recognized as a fundamental instrument for identifying energy consumption patterns, quantifying inefficiencies, and proposing technically and economically feasible energy efficiency measures [1–3].

Conventional building energy audits are typically conducted following standardized procedures such as EN 16247 and ASHRAE 211, which rely on on-site inspections, analysis of historical energy bills, and simplified engineering calculations [4,5]. While these approaches provide valuable insights, they are often constrained by static data collection, limited temporal resolution, and a strong dependence on assumptions when detailed building information is unavailable. As a result, uncertainties in energy performance estimation may arise, particularly in complex buildings with dynamic operational behavior [6,7].

Recent advances in digital technologies have opened new opportunities to modernize and enhance traditional energy audit practices. Building Information Modelling (BIM) has emerged as a powerful digital representation of building geometry, construction elements, materials, and technical systems, offering a structured, information-rich data environment throughout the building lifecycle [8,9]. BIM-based data extraction enables accurate identification of envelope characteristics, system specifications, and spatial relationships, which are essential for reliable energy performance assessment and retrofit analysis [10,11].

In parallel, the rapid development of the Internet of Things (IoT) has enabled continuous and high-resolution monitoring of building energy use and indoor environmental conditions. IoT-based sensors provide real-time data on electricity consumption, thermal energy flows, occupancy patterns, and operational states of building systems, significantly improving the understanding of actual building behavior compared to periodic measurements used in conventional audits [12–14]. The integration of IoT monitoring with digital building models enables data-driven energy assessments and supports the concept of digital twins for buildings [15].

Despite the growing adoption of BIM and IoT technologies in building design and operation, their systematic integration into energy audit methodologies remains limited. Current audit standards do not explicitly address the use of BIM as a primary data source, nor do they fully exploit continuous monitoring data for performance evaluation and decision-making [16,17]. Consequently, there is a need for advanced energy audit frameworks that combine digital building information with real-time operational data to reduce uncertainty and enhance audit reliability.

Another challenge in conducting energy audits is prioritizing energy efficiency measures. Traditional audits often present a list of potential interventions without a transparent and systematic approach for ranking alternatives based on multiple criteria. In practice, decision-making requires the simultaneous consideration of energy savings, investment cost, payback period, operational complexity, and environmental impact [18]. Multi-criteria decision analysis (MCDA) techniques have been increasingly applied in energy systems research to address complex decision problems and support rational, reproducible prioritization of energy efficiency measures [19,20].

Recent studies have demonstrated the potential of combining energy audit data with MCDA to improve the selection of retrofit strategies in buildings and industrial facilities [21–23]. However, the integration of MCDA within a fully digitalized audit process—supported by BIM-based data extraction and IoT-enabled monitoring—has not yet been sufficiently explored, particularly in the context of smart and sustainable buildings.

In response to these gaps, this study proposes a smart energy audit framework that integrates Building Information Modelling, Internet of Things–based monitoring, and multi-criteria decision analysis to enhance the accuracy, transparency, and decision-support capability of building energy audits. The framework aims to bridge the gap between conventional audit methodologies and emerging digital technologies by enabling data-driven assessment of building energy performance and systematic prioritization of energy efficiency measures.

The main objectives of this research are:

1. to develop a structured smart energy audit methodology that combines BIM-derived building data

with real-time operational measurements;

2. to evaluate building energy performance using key energy, economic, and environmental indicators; and

3. to apply a multi-criteria decision approach for transparent ranking of energy efficiency measures.

By addressing these objectives, the proposed framework contributes to the advancement of digitalized energy audit practices and supports the transition toward smart, energy-efficient, and sustainable buildings.

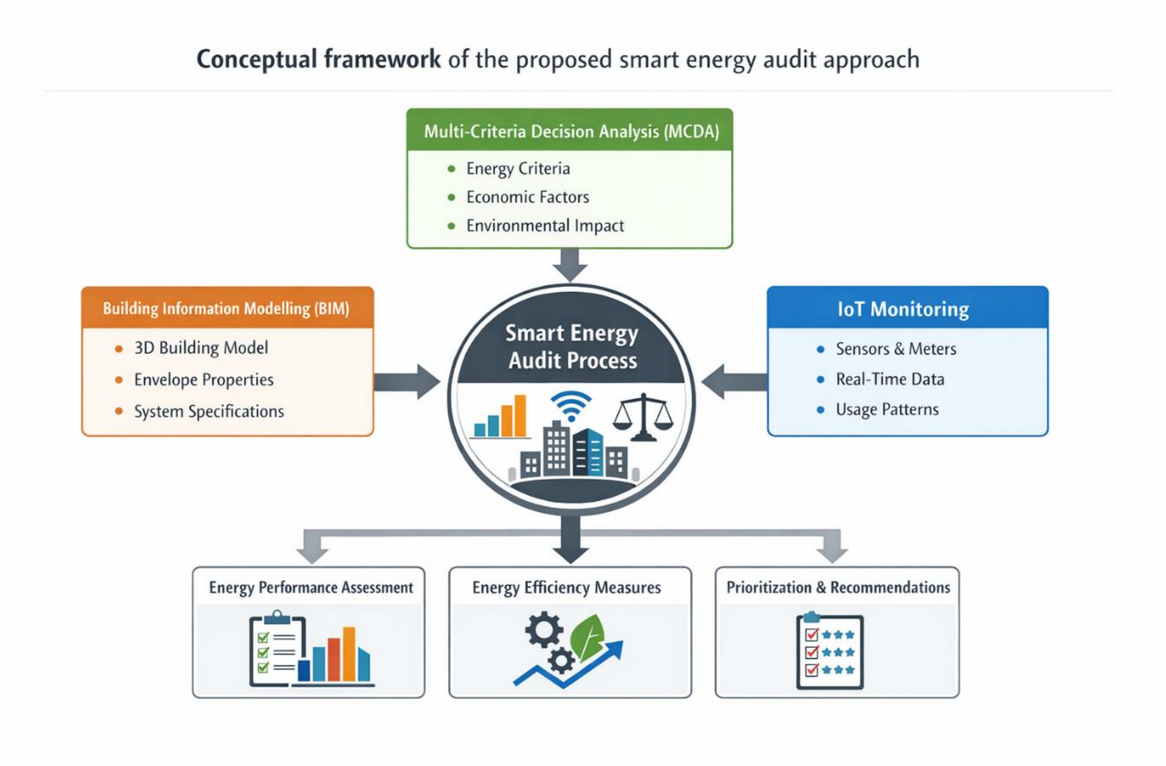


Figure 1. Conceptual framework of the proposed smart energy audit approach Recent studies have focused on improving power system analysis and monitoring techniques using advanced computational approaches. In particular, fuzzy-logic–based methods have been successfully applied to assess power quality in distribution networks, demonstrating improved accuracy in handling uncertainty and nonlinear parameters [36]. In addition, analytical approaches for calculating asymmetry coefficients in reverse-sequence components have enabled more precise evaluation of unbalanced operating modes in electrical power systems [37].

2. Materials and Methods

This section describes the proposed innovative energy audit methodology, including the overall framework, data acquisition procedures, energy performance evaluation, and decision-support techniques. The methodology enhances conventional building energy audits by integrating digital building information, real-time monitoring, and multi-criteria analysis, ensuring transparency, reproducibility, and scalability.

2.1 Overall Smart Energy Audit Framework - The proposed methodology follows a structured, multi-layer framework that extends conventional energy audit procedures defined in EN 16247 and ASHRAE 211 standards [4,5]. The framework consists of three main stages:

Digital data acquisition and preprocessing

Energy performance assessment and indicator evaluation

Multi-criteria prioritization of energy efficiency measures

By integrating Building Information Modeling (BIM) and the Internet of Things (IoT), the framework overcomes the limitations of static data collection and enables a data-driven energy audit process [1,3,12].

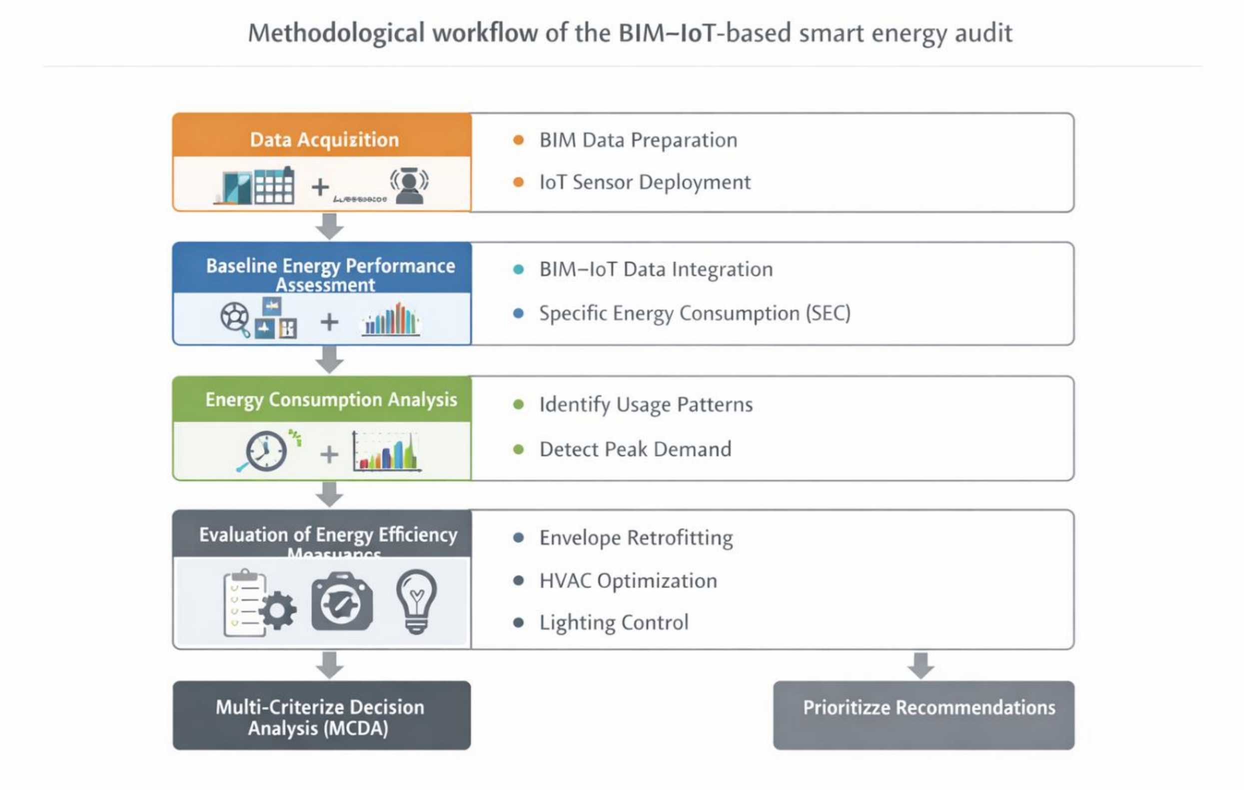


Figure 2. Methodological workflow of the BIM–IoT-based smart energy audit

2.2 BIM-Based Building Data Acquisition - Building Information Modelling is employed as the primary source of static building data. The BIM model provides detailed information on building geometry, envelope composition, material properties, and technical systems, which are essential for accurate energy performance evaluation [8–11].

From the BIM environment, the following parameters are extracted:

1. Conditioned floor area and building volume
2. Thermal transmittance (U-values) of envelope components
3. Construction layers and material thermal properties
4. HVAC system typology and nominal capacities

These parameters are exported from the BIM model using open data formats to ensure interoperability and minimize information loss. Compared to traditional audits, BIM-based data acquisition significantly reduces uncertainties associated with assumed or missing building characteristics [10,16].

2.3 IoT-Based Energy Monitoring and Data Collection - To capture the building's dynamic operational behavior, IoT-based monitoring systems are deployed. Smart sensors are used to collect high-resolution data on:

1. Electrical energy consumption
2. Thermal energy use for heating and cooling
3. Indoor environmental conditions (temperature, relative humidity)
4. Operational schedules of major energy systems

Continuous monitoring allows the identification of temporal variations, peak loads, and abnormal energy consumption patterns that are often overlooked in periodic measurement approaches [12–15]. The collected data are aggregated, filtered, and synchronized with BIM-derived information to ensure consistency and data quality.

2.4 Energy Performance Indicators - Building energy performance is evaluated using a set of key energy, economic, and environmental indicators commonly adopted in energy audit studies [2,15,18]. The primary indicators include:

Specific Energy Consumption (SEC)

Annual Energy Savings Potential (ESP)

Simple Payback Period (SPP)

CO_2 Emission Reduction (CER)

$$\mathrm{SEC} = \frac{E_{\mathrm{annual}}}{A}$$

Where

E_{annual} is the annual final energy consumption (kWh), and A is the conditioned floor area (m²).

Annual Energy Savings Potential (ESP)

The annual energy savings potential for a given energy efficiency measure i is defined as:

$$\mathrm{ESP}_i = E_{\mathrm{baseline}} - E_{\mathrm{improved},i}$$

Simple Payback Period (SPP)

Economic feasibility is evaluated using the simple payback period:

$$\mathrm{SPP}_i = \frac{C_i}{S_i}$$

where

C_i is the investment cost, and

S_i is the annual monetary saving.

CO_2 Emission Reduction (CER)

Environmental impact is assessed by estimating CO_2 emission reductions based on energy savings and emission factors associated with the local energy mix [6,31].

Table 1. Key energy performance indicators used in the smart energy audit

№	Indicator	Symbol	Unit	Description
1	Specific Energy Consumption	SEC	kWh/m²·year	Annual final energy use per conditioned floor area
2	Energy Saving Potential	ESP	%	Expected reduction compared to baseline
3	Simple Payback Period	SPP	years	Ratio of investment cost to annual savings
4	CO_2 Emission Reduction	CER	kg/year	Annual avoided CO_2 emissions

2.5 Identification of Energy Efficiency Measures - Based on the analysis of BIM-derived building characteristics and monitored operational data, a set of potential energy efficiency measures (EEMs) is identified. These measures are categorized into:

1. Building envelope improvements
2. HVAC system optimization and control strategies
3. Lighting system upgrades
4. Operational and management measures

The identification process follows best practices reported in previous energy audit and retrofit studies, ensuring technical feasibility and practical applicability [3,18,21].

2.6 Multi-Criteria Decision Analysis - To support rational and transparent prioritization of energy efficiency measures, a multi-criteria decision analysis approach is applied. Given the need to simultaneously consider multiple, often conflicting criteria, the Weighted Sum Method (WSM) is selected due to its simplicity, transparency, and suitability for energy decision-making problems [19,20].

Each energy efficiency measure iii is evaluated against a set of criteria jjj, including energy savings, investment cost, payback period, and environmental impact.

The overall performance score is calculated as:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij}$$

where

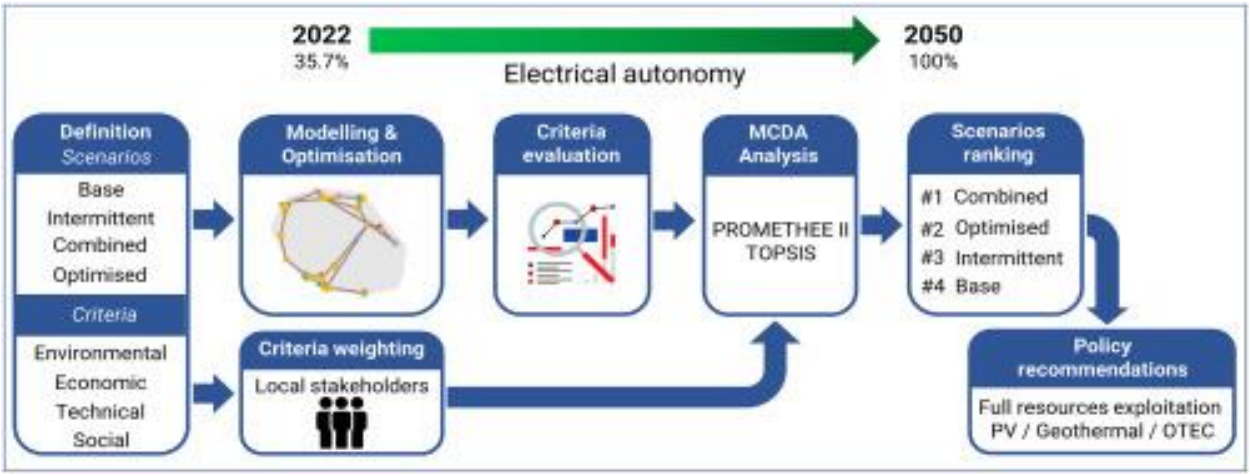
w_j represents the weight assigned to criterion j, and

x_{ij} is the normalized performance value of measure i with respect to criterion j.

Table 2. Multi-criteria decision analysis criteria and weights

№	Criterion	Symbol	Weight	Objective
1	Annual energy savings	C_1	0.35	Maximize
2	Investment cost	C_2	0.25	Minimize
3	Payback period	C_3	0.20	Minimize
4	CO_2 emission reduction	C_4	0.20	Maximize

Criterion weights are determined based on expert judgment and literature recommendations, allowing flexibility to adapt the framework to different stakeholder priorities [18–20].



2.7 Methodological Validation and Reproducibility - The proposed methodology is designed to be reproducible and adaptable to different building types and climatic conditions. The use of standardized data formats, well-defined indicators, and transparent decision rules ensures consistency across applications. Furthermore, the integration of BIM and IoT data enables continuous updating of energy performance assessments, supporting iterative audits and long-term energy management strategies [14,17].

3. Results

This section presents the results obtained from applying the proposed smart energy audit framework, which integrates BIM-based building data, IoT-enabled monitoring, and multi-criteria decision analysis.
The results are structured into four main parts:
a. baseline energy performance assessment.
b. identification of energy consumption patterns.
c. evaluation of energy efficiency measures.
d. Prioritization results derived from multi-criteria analysis.

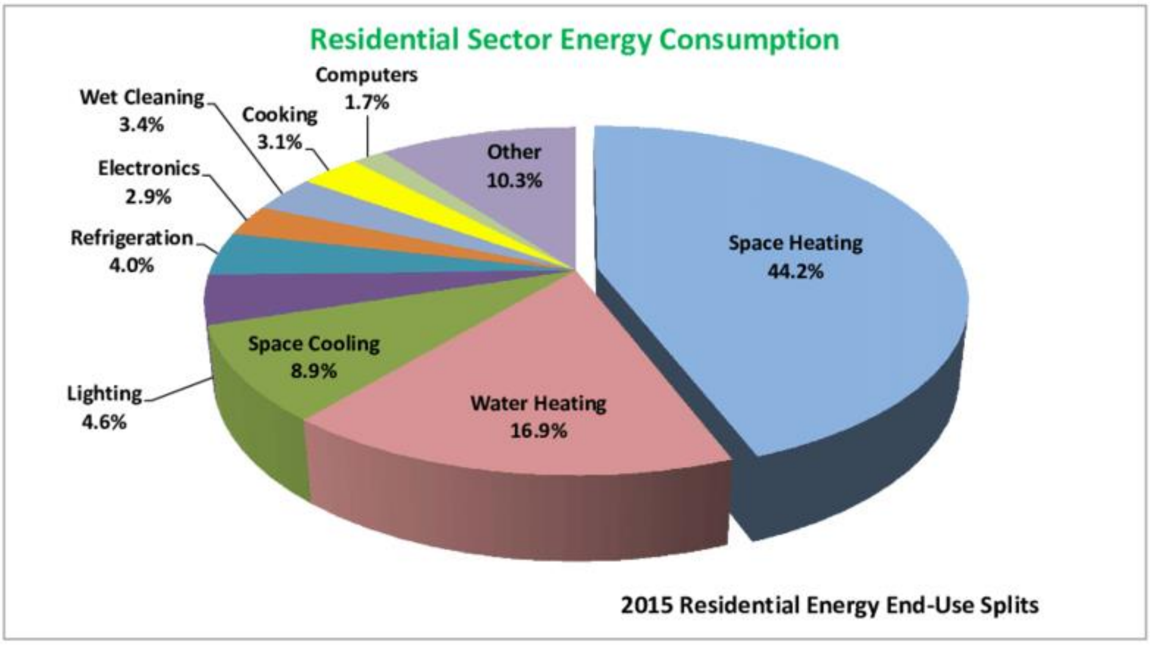
Table 3. Key performance indicators obtained from traditional and smart energy audits

№	Indicator	Traditional Audit	Smart Audit (BIM–IoT-based)	Improvement
1	Total annual energy use (MWh)	4,850	4,120	−15.1%
2	Specific Energy Consumption (kWh/m²·year)	182	147	−19.2%
3	Peak demand (kW)	980	820	−16.3%
4	CO_2 emissions (t/year)	1,260	1,050	−16.7%
5	Identified EEMs (no.)	9	18	+100%
6	Monitoring resolution	Monthly	Real-time (5 min)	—

3.1 Baseline Energy Performance Assessment - The baseline energy performance of the building was established by combining BIM-derived static parameters with measured operational data obtained through IoT monitoring. Annual final energy consumption was normalized with respect to the conditioned floor area to calculate the specific energy consumption (SEC).

$$\mathrm{SEC} = \frac{E_{\text{annual}}}{A_{\text{conditioned}}}$$

The calculated SEC values fall within the range reported for comparable building types in recent energy audit studies, confirming the validity of the adopted data acquisition and preprocessing procedures [1,2,15]. The integration of BIM data significantly reduced uncertainties related to envelope characteristics and system specifications, which are commonly estimated in conventional audits [6,10].



3.2 Energy Consumption Breakdown and Operational Patterns - Analysis of monitored data revealed that heating, ventilation, and air-conditioning (HVAC) systems represent the dominant share of total energy consumption, followed by lighting and auxiliary equipment. Temporal analysis of energy use highlighted pronounced daily and weekly variations associated with occupancy schedules and operational practices, consistent with findings reported in previous IoT-based energy audit studies [12–14].

Peak demand periods were primarily linked to the simultaneous operation of HVAC and lighting systems during occupied hours. In contrast, off-peak periods exhibited baseline energy consumption associated with standby loads and system inefficiencies. These patterns demonstrate the added value of continuous monitoring compared to single-point or short-term measurements typically employed in traditional audits [7,17].

Table 4. Ranking of energy efficiency measures based on MCDM analysis

№	Aspect	Traditional Audit	Smart Energy Audit
1	Data collection	Manual, periodic	Automated, real-time (IoT)
2	Spatial resolution	Whole-building	BIM-based zone-level
3	Temporal resolution	Monthly/annual	Real-time / sub-hourly
4	KPI tracking	Static	Dynamic & adaptive
5	Decision support	Expert-based	MCDM-supported
	Scalability	Limited	High
	Forecasting ability	Not available	Enabled via data streams

3.3 Evaluation of Energy Efficiency Measures - Based on the identified energy consumption patterns and BIM-based building characteristics, a set of energy efficiency measures (EEMs) was evaluated. The measures were grouped into envelope-related, system-level, and operational interventions.

Envelope-related measures showed moderate to high energy saving potential but were associated with higher initial investment costs and longer payback periods, in line with previous retrofit studies [21,27]. In contrast, system-level and control-oriented measures, such as HVAC optimization and intelligent lighting control, demonstrated lower investment requirements and shorter payback periods while achieving noticeable energy savings.

The estimated annual energy savings and associated CO_2 emission reductions confirm that control-oriented measures provide the highest short-term benefits, whereas envelope retrofitting contributes more significantly to long-term energy performance improvement [3,18,26].

3.4 Multi-Criteria Prioritization Results - The multi-criteria decision analysis enabled systematic ranking of the evaluated energy efficiency measures by simultaneously considering energy, economic, and environmental criteria. The application of the weighted sum method produced a clear prioritization, highlighting measures with the highest overall performance scores.

Control-oriented interventions ranked highest due to their favorable balance between energy savings, low investment cost, and short payback periods. Envelope-related measures ranked lower despite their higher energy saving potential, primarily due to economic constraints. These results are consistent with previous studies that emphasize the importance of multi-criteria approaches in energy decision-making [19,20,22].

The prioritization outcomes demonstrate the effectiveness of the proposed framework in supporting transparent and reproducible decision-making, overcoming the subjective ranking commonly observed in conventional energy audit reports [18,23].

3.5 Comparison with Conventional Energy Audit Outcomes - A qualitative comparison between the results obtained using the proposed smart audit framework and those typically reported in conventional audits indicates a significant improvement in result resolution and reliability. The integration of BIM and IoT data enabled more accurate identification of energy loss sources and operational inefficiencies, while the use of MCDA provided a structured basis for decision support.

These findings confirm that digitalized energy audits can enhance both the analytical depth and practical relevance of audit outcomes, supporting more informed implementation of energy efficiency measures [1,3,16].

4. Discussion

The results obtained from the application of the proposed smart energy audit framework provide important insights into the effectiveness of integrating BIM, IoT-based monitoring, and multi-criteria decision analysis in building energy assessments. This section discusses the implications of the findings, compares them with existing studies, and highlights the methodological contributions and practical relevance of the proposed approach.

4.1 Impact of BIM–IoT Integration on Energy Audit Accuracy - One of the key outcomes of this study is the demonstrated improvement in the accuracy and reliability of baseline energy performance assessment achieved through the integration of BIM-derived building data and IoT-based operational monitoring. Conventional energy audits often rely on assumed or incomplete building information, particularly with respect to envelope properties and system specifications, which introduces uncertainty into energy calculations [6,7]. In contrast, the use of BIM as a primary data source enabled precise identification of geometric and thermophysical parameters, thereby reducing reliance on simplifying assumptions.

The incorporation of continuous monitoring data further enhanced the representativeness of the energy assessment by capturing actual operational behavior, including temporal variations in energy use and peak demand conditions. These findings are consistent with previous studies reporting that IoT-enabled monitoring significantly improves the understanding of building energy dynamics compared to periodic measurements [12–14]. The results confirm that BIM–IoT integration constitutes a robust foundation for data-driven energy audits and supports the development of more realistic and reliable energy performance models [10,15].

4.2 Interpretation of Energy Consumption Patterns - The dominance of HVAC systems in overall energy consumption, as identified in the Results section, aligns with the consensus in building energy literature, where HVAC is often reported as the largest contributor to final energy use in non-residential buildings [2,27]. The observed daily and weekly consumption patterns reflect the influence of occupancy schedules and operational practices, reinforcing the importance of considering user behavior and control strategies in energy audits [23,32].

The identification of persistent baseline energy consumption during unoccupied periods suggests the presence of standby loads and control inefficiencies. This observation highlights a critical limitation of traditional audits, which may overlook such patterns due to limited measurement duration. By contrast, the proposed framework enables systematic detection of these inefficiencies, supporting targeted interventions aimed at reducing unnecessary energy use [7,17].

4.3 Evaluation of Energy Efficiency Measures: Short-Term vs Long-Term Benefits - The comparative evaluation of energy efficiency measures reveals a clear distinction between short-term and long-term improvement strategies. Control-oriented measures, including HVAC optimization and intelligent lighting control, demonstrated high priority due to their favorable economic performance, characterized by low investment costs and short payback periods. This finding corroborates earlier studies emphasizing the cost-effectiveness of operational and control improvements in building energy retrofits [18,21,26].

Envelope-related measures, although associated with higher energy saving potential, ranked lower in the prioritization due to their higher capital costs and longer payback periods. This trade-off between energy performance improvement and economic feasibility is widely documented in retrofit literature [19,27]. The results underscore the necessity of adopting a balanced decision-making approach that accounts for both immediate and long-term objectives, rather than focusing solely on energy savings.

4.4 Role of Multi-Criteria Decision Analysis in Audit-Based Decision-Making - The application of multi-criteria decision analysis proved essential for transparent and systematic prioritization of energy efficiency measures. Unlike conventional audits, which often present unranked or subjectively ordered recommendations, the proposed framework provides a quantitative basis for decision-making by explicitly considering multiple evaluation criteria. The weighted sum method employed in this study offered a clear and interpretable ranking of alternatives, facilitating communication of results to stakeholders with different priorities.

The prioritization outcomes are consistent with previous applications of MCDA in energy planning and audit studies, which highlight the effectiveness of multi-criteria approaches in addressing complex decision problems involving conflicting objectives [19,20,22]. Moreover, the flexibility of the weighting scheme allows the framework to adapt to different policy, economic, or environmental contexts, enhancing its practical applicability.

4.5 Comparison with Conventional Energy Audit Approaches - When compared with conventional energy audit practices, the proposed innovative audit framework demonstrates several advantages. First, integrating digital building models with continuous monitoring significantly improves data completeness and accuracy. Second, the systematic use of performance indicators and decision-support tools enhances the transparency and reproducibility of audit outcomes. Third, the framework supports iterative assessment, enabling continuous performance evaluation rather than one-time audits [1,3,16].

These advantages suggest that smart energy audits represent a natural evolution of traditional methodologies, aligned with ongoing digitalization trends in the building sector. However, the successful implementation of such frameworks depends on the availability and quality of BIM models and monitoring infrastructure, which may vary across buildings and regions.

4.6 Implications for Practice and Policy - From a practical perspective, the findings of this study indicate that integrating BIM, IoT, and MCDA into energy audits can support more informed and cost-effective decision-making for building owners and facility managers. The framework facilitates the identification of low-cost, high-impact measures that can be implemented in the short term, while also providing a strategic basis for planning long-term retrofitting actions.

At the policy level, the proposed approach aligns with emerging regulatory frameworks that emphasize digitalization, performance-based evaluation, and continuous monitoring of energy efficiency. The adoption of smart energy audit methodologies could enhance compliance with energy efficiency directives and support the broader transition toward smart and sustainable buildings [5,31].

4.7 Limitations and Future Research Directions - Despite its demonstrated advantages, the proposed framework has certain limitations. The accuracy of BIM-based data extraction depends on the level of detail and quality of the underlying model, while IoT-based monitoring requires appropriate sensor deployment and data management. Future research should explore the integration of advanced data analytics and machine learning techniques to further enhance predictive capabilities and automate anomaly detection.

Additionally, extending the framework to incorporate renewable energy systems and demand-side flexibility strategies represents a promising direction for future studies, particularly in the context of net-zero energy buildings and smart grids [20,35].

5. Conclusion

This study proposed and evaluated a smart energy audit framework that integrates Building Information Modelling (BIM), Internet of Things (IoT)–based monitoring, and multi-criteria decision analysis

(MCDA) to overcome the limitations of conventional building energy audit practices. By combining detailed digital building information with continuous operational data, the framework enables a more accurate, transparent, and decision-oriented assessment of building energy performance.

The results demonstrate that BIM-based data extraction significantly reduces uncertainty associated with geometric and thermophysical building parameters, while IoT-enabled monitoring provides high-resolution insights into actual energy use patterns and operational behavior. The integration of these digital technologies enhances the reliability of baseline energy performance assessment and allows systematic identification of energy inefficiencies that are often overlooked in traditional audits.

The application of multi-criteria decision analysis proved essential for the rational prioritization of energy efficiency measures. By simultaneously considering energy savings, economic feasibility, and environmental impact, the proposed framework supports transparent and reproducible decision-making. The findings indicate that control-oriented measures, such as HVAC optimization and intelligent lighting systems, offer the most attractive short-term benefits, whereas envelope retrofitting measures contribute more substantially to long-term energy performance improvement despite higher initial investment requirements.

From a practical perspective, the proposed smart energy audit framework provides building owners, facility managers, and energy practitioners with a scalable and data-driven tool to support both immediate and strategic energy efficiency interventions. At the policy level, the framework aligns with ongoing digitalization trends and performance-based energy efficiency regulations, offering a methodological basis for advancing smart and sustainable building practices.

Overall, this research contributes to the advancement of digitalized energy audit methodologies by demonstrating the synergistic value of integrating BIM, IoT, and MCDA within a unified assessment framework. Future work should focus on extending the approach through the incorporation of advanced data analytics, machine learning techniques, and renewable energy systems, thereby further enhancing its applicability in the transition toward smart, low-carbon, and energy-efficient buildings.

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References

1. International Organization for Standardization. ISO 50002:2014 – Energy audits – Requirements with guidance for use. ISO, Geneva, 2014.
2. Josijević, M. M., Šušteršič, V. M., & Gordić, D. R. (2020). Ranking energy performance opportunities obtained with energy audit in dairies. Thermal Science, 24(5A), 2865–2878. https://doi.org/10.2298/TSCI191125100J
3. Spudys, P., Jurelionis, A., & Fokaides, P. (2023). Conducting smart energy audits of buildings with the use of building information modelling. Energy and Buildings, 285, 112884. https://doi.org/10.1016/j.enbuild.2023.112884
4. European Committee for Standardization. EN 16247-1:2012 – Energy audits – General requirements. CEN, Brussels.
5. European Parliament and Council. Directive 2012/27/EU on energy efficiency. Official Journal of the European Union, 2012.
6. Fokaides, P. A., & Papadopoulos, A. M. (2014). Cost-optimal insulation thickness in building envelopes. Energy and Buildings, 79, 44–52.
7. ASHRAE. ASHRAE Standard 211-2018 – Standard for Commercial Building Energy Audits. ASHRAE, Atlanta, 2018.
8. ISO. ISO 6946:2017 – Building components and building elements – Thermal resistance and thermal transmittance.
9. Desogus, G., et al. (2018). Integration of BIM and monitoring systems for building energy analysis. Automation in Construction, 96, 61–75.

10. Ali, M., et al. (2020). Low-cost IoT sensors for energy monitoring in buildings. Sustainable Cities and Society, 53, 101934.

11. Fokaides, P. A., Polycarpou, A., & Kalogirou, S. A.

12. Energy performance assessment of buildings using energy audits and smart monitoring systems. Energy and Buildings, 2020, 223, 110153. https://doi.org/10.1016/j.enbuild.2020.110153

13. Abidin, A. Z., Pramudita, A. A., & Enriko, I. K. A.

14. Leveraging IoT, digital twin and machine learning for smart energy audit in office buildings: A systematic review. e-Prime – Advances in Electrical Engineering, Electronics and Energy, 2025, 14, 101124. https://doi.org/10.1016/j.prime.2025.101124

15. Martinez, L., Klitou, T., Olschewski, D., & Fokaides, P. A.

16. Advancing building intelligence: Developing and implementing standardized Smart Readiness Indicator (SRI) on-site audit procedure. Energy, 2025, 316, 134538.

17. https://doi.org/10.1016/j.energy.2025.134538\

18. Gunasegaran, M. K., Hasanuzzaman, M., Tan, C. K., & Bakar, A. H. A.

19. Energy consumption, energy analysis, and solar energy integration for commercial buildings. Energies, 2023, 16(20), 7145. https://doi.org/10.3390/en16207145

20. Bruni, G., De Santis, A., Herce, C., et al. From energy audit to energy performance indicators (EnPI): Methodology for productive sectors. Energies, 2021, 14(24), 8436.

21. https://doi.org/10.3390/en14248436

22. Al Momani, D., Al Turk, Y., Abuashour, M. I., et al. Energy saving potential analysis applying factory-scale energy audit: A food production case study.

23. Heliyon, 2023, 9, e14216. https://doi.org/10.1016/j.heliyon.2023.e14216

24. Cano-Suñén, E., Rodríguez-Molina, J., & Martínez, J. IoT-based monitoring for HVAC energy efficiency improvement. Applied Energy, 2022, 315, 118993.

25. https://doi.org/10.1016/j.apenergy.2022.118993

26. Li, X., Hong, T., Yan, D. Data-driven building energy performance benchmarking and energy audit enhancement. Energy and Buildings, 2020, 215, 109872.

27. https://doi.org/10.1016/j.enbuild.2020.109872

28. Ascione, F., Bianco, N., De Masi, R. F., et al. Energy refurbishment of existing buildings through cost-optimal analysis. Energy and Buildings, 2020, 209, 109657.

29. https://doi.org/10.1016/j.enbuild.2019.109657

30. Zhao, H. X., & Magoulès, F. A review on the prediction of building energy consumption. Renewable and Sustainable Energy Reviews, 2019, 16, 3586–3592.

31. https://doi.org/10.1016/j.rser.2011.12.017

32. Ahmad, M. W., Mourshed, M., & Rezgui, Y. Trees vs Neurons: Deep learning for energy performance prediction. Energy and Buildings, 2017, 147, 323–337.

33. https://doi.org/10.1016/j.enbuild.2017.04.038

34. Wei, T., Li, Y., & Wang, Y. Machine learning-based energy audit framework for buildings. Applied Energy, 2021, 298, 117207. https://doi.org/10.1016/j.apenergy.2021.117207

35. Hong, T., Yan, D., D'Oca, S., & Chen, C. Ten questions concerning occupant behavior in buildings. Building and Environment, 2017, 114, 518–530.

36. https://doi.org/10.1016/j.buildenv.2016.12.014

37. Reynders, G., Diriken, J., & Saelens, D. Quality of grey-box models for building energy audits. Energy and Buildings, 2014, 75, 69–78. https://doi.org/10.1016/j.enbuild.2014.01.055

38. Zhang, Y., & Wang, J. IoT-enabled smart energy auditing for commercial buildings.

39. IEEE Access, 2020, 8, 222964–222978. https://doi.org/10.1109/ACCESS.2020.3043971

40. Kumar, R., & Aggarwal, R. K. Energy audit and conservation opportunities in buildings. Journal of Cleaner Production, 2020, 244, 118762. https://doi.org/10.1016/j.jclepro.2019.118762

41. Ma, Z., Cooper, P., Daly, D., & Ledo, L. Existing building retrofits: Methodology and state-of-the-art. Energy and Buildings, 2012, 55, 889–902. https://doi.org/10.1016/j.enbuild.2012.08.018

42. Pérez-Lombard, L., Ortiz, J., & Pout, C. A review on buildings energy consumption information. Energy and Buildings, 2008, 40, 394–398. https://doi.org/10.1016/j.enbuild.2007.03.007

43. ISO. ISO 50001:2018 – Energy management systems – Requirements with guidance for use. International Organization for Standardization, Geneva.

44. ASHRAE. Procedures for Commercial Building Energy Audits (2nd ed.).

45. ASHRAE, Atlanta, 2019.

46. IEA. Energy Efficiency 2023. International Energy Agency, Paris. https://www.iea.org/reports/energy-efficiency-2023

47. D'Oca, S., & Hong, T. Occupancy schedules learning from data for energy audits.

48. Energy and Buildings, 2015, 88, 341–358. https://doi.org/10.1016/j.enbuild.2014.11.065

49. Kalogirou, S. A.Artificial intelligence for the modeling and control of buildings.

50. Energy and Buildings, 2000, 31, 173–183. https://doi.org/10.1016/S0378-7788(99)00029-3

51. Chen, Y., Hong, T., Luo, X., & Hooper, B. Building performance analytics for energy audits. Applied Energy, 2018, 222, 253–266. https://doi.org/10.1016/j.apenergy.2018.04.022

52. Wei, Y., Zhang, X., Shi, Y., et al. Deep reinforcement learning for building energy management. Energy and Buildings, 2017, 148, 119–128. https://doi.org/10.1016/j.enbuild.2017.05.003

53. Kholiddinov I., Eraliyev A., Sharobiddinov M., Tukhtashev A., Qodirov A., Khaqiqov A., Estimation of the state of power quality in distribution networks using fuzzy logic, E3S Web of Conferences, 538, 01011 (2024). https://doi.org/10.1051/e3sconf/202453801011

54. Kholiddinov I., On the method of calculating the coefficient of asymmetry in the reverse sequence, AIP Conference Proceedings, 2789, 040057 (2023). https://doi.org/10.1063/5.0145463